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Receiving unemployment benefits may have positive effects on the health of the unemployed

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ABSTRACT

Research suggests that job loss can cause illness and premature death. This raises the question of whether unemployment benefit programs, which aim to alleviate the financial stress of job loss, can protect the health of the unemployed. To investigate the impact of unemployment benefits on health after job loss, we used data from 1984 to 2009 from the Panel Study of Income Dynamics (PSID). We found that receiving unemployment benefits significantly reduces the probability of reporting poor health in the year after job loss by around 5 percentage points. The health promoting effects of unemployment benefits are robust across multiple model specifications and controls for pre-existing differences between benefit recipients and non-recipients. Our results add to an increasing body of literature that suggests that social policies can have unanticipated health effects.

1. INTRODUCTION

Growing evidence suggests that job loss can lead to increased probability of illness and premature death (1-7). This raises the question of whether unemployment benefit programs, which aim to alleviate the financial stress of job loss, could themselves have unintended consequences for health. If the detrimental health effects of unemployment are in part due to income loss and financial insecurity, unemployment benefits may offer a mechanism to prevent or reduce some of the negative health effects of job loss. Although unemployment benefit programs are not explicitly designed to improve health, a number of recent studies have demonstrated that social policies not motivated by health concerns, such as the earned income tax credit, US welfare reform and the food stamp program, have both positive and negative consequences for health (8-11).

The US Federal-State Unemployment Insurance Program provides temporary wage replacement for eligible workers who become unemployed through no fault of their own. Each state operates its own program but must follow certain general rules established by the Federal Government relating to coverage and eligibility. Most research on this program has focused on impacts on earnings, consumption and unemployment duration (12-14), but few studies have examined potential health consequences.

Identifying the effect of unemployment benefits on health is challenging, however, due to strong selection into job loss as well as unemployment benefit receipt and duration. Individuals in poor health are not only more likely to experience an unemployment spell than comparatively healthier workers (15, 16); given strict eligibility requirements to qualify for benefits, they are also likely to differ from unemployed non-recipients in a number of key characteristics associated with health, such as income and education (17, 18).

While some studies suggest that unemployment benefits may ameliorate some of the negative health effects of job loss (19-21), prior studies have not accounted for pre-existing differences between benefit recipients and non-recipients. A potential concern is therefore that benefit recipients are *a priori* in comparatively better health than their non-recipient counterparts.

In this study, we use 20 survey waves of the Panel Study of Income Dynamics (PSID) from 1984 to 2009 to investigate the impact of unemployment benefits on the probability of reporting poor health after job loss. We test this hypothesis in various model specifications (including propensity score matching and two-stage least squares) that aim to adjust for the bias arising from pre-existing differences between benefit recipients and non-recipients. While neither approach can fully establish that unemployment benefits have a causal effect on health, these methodological approaches partly address concerns of selection in earlier studies. Findings may be useful for policy makers and health practitioners considering the potential health implications of future reforms to unemployment benefit programs and similar social protection policies.

2. BACKGROUND

Unemployment benefit programs may influence the health of displaced workers through several mechanisms. In the short term, benefits compensate for the loss of earnings associated with job loss and smooth consumption during unemployment spells (12). This may enable workers to purchase health-promoting goods and services such as healthy food and health insurance coverage, as well as reduce some of the psychosocial stress associated with financial losses. On the other hand, unemployment benefits may reduce the marginal incentive to search for a job, increasing the incidence and duration of non-employment (14, 22-24). This could lead to skill depreciation and negative career effects, which may be detrimental for health in the long-run.

A small number of studies have examined the impact of unemployment benefits on health. Rodriguez used data from the United States, Germany and Britain and found that unemployed workers receiving different types of government entitlement benefits (including unemployment benefits) reported similar health status as full-time employed workers, suggesting that such support programs can buffer the health effects of job loss (Rodriguez 2001). Other studies have reported protective effects of government entitlement benefits for depression symptoms among unemployed women (25); poor self-rated health among minimum and medium skill level jobs (21); and poor mental health among unemployed workers in Spain (26). While most of these studies find a positive association between unemployment benefits and health, a key limitation is the lack of attention to selection.

Job losers do not automatically qualify to receive unemployment benefits, but rather, must meet several monetary and non-monetary eligibility criteria (27). Displaced workers must also file claims with state unemployment benefit agencies to receive benefits. An implication is that not all eligible displaced workers actually claim benefits. In fact, unemployment benefit programs in the United States have historically had low take-up rates, with 34.8% of the unemployed applying for benefits in 2005 and only 23.9% actually receiving benefits, according to data from the Current Population Survey (CPS) (18). 51.9% of the unemployed who did not apply for unemployment benefits did so because they believed themselves to be ineligible; 17.8% did not apply because of reasons related to attitude, lack of understanding or other barriers; and 5.3% reported that they did not apply because they were retired, ill or disabled.

Because of eligibility rules and the need to apply for benefits, several important differences arise between unemployed individuals who receive benefits and those who do not. Compared to non-recipients, unemployed workers receiving unemployment benefits are more likely to be educated, higher-earners and to have previously received benefits (17). This selection makes it particularly challenging to establish whether unemployment benefits have an impact on health. prior studies have not fully accounted for these pre-existing differences between benefit recipients and non-recipients. A potential concern is that benefit recipients are in comparatively better health than their non-recipient counterparts prior to receiving benefits. Recent studies circumvent this problem by exploiting variations in state unemployment benefit program design (28, 29). However, these studies did not incorporate information on receipt of benefits at the individual level, making it unclear whether receiving unemployment benefits plays a critical role in the causal pathway linking job loss and health. The present study aims to shed light on this question and address some of the limitations from previous studies by applying multiple modelling strategies using a longitudinal sample representative of the United States population.

3. METHODS

3.1 Data

We use data from the PSID, the longest running longitudinal household survey in the world, which collects data on employment status, demographics, and health (30). Data were collected annually up until 1997, after which the PSID shifted to a biennial design. The analysis presented is based on the sample of unemployment spells experienced by working-age (18-65 years old) heads of household from the 1984 (the year health measures were introduced) through 2009 survey waves. Observations with missing data were excluded from the analysis leaving a sample of 4,247 unemployment spells, 875 of which received unemployment benefits (results from a sample of all unemployment spells yielded similar results).

The PSID measures health using the self-rated health item, a subjective indicator that captures individuals' perceptions of their health using Likert scales. Respondents are asked to rate their own health on a scale ranging from 'excellent' (1) to 'very good' (2), 'good' (3), 'fair' (4), and 'poor' (5). We collapse the scale into a binary variable, where categories 4 and 5 indicate poor health. This binary indicator has been shown to be a strong predictor of objective measures of health, including the risk of death (31-33).

We extracted data on employment status from each survey wave. Based on available information we constructed binary variables that indicate whether an unemployment spell occurred at some point in the previous year, and whether the individual received unemployment benefits following that spell.

Other variables used in the analysis include age, gender, race (white, black, other), education level (high school, college, above), marital status (married, single, separated, divorced, widowed), and household size. Two other individual level variables were lagged by 2 years: the binary indicator of poor health and the natural log of family income. Income is lagged to avoid simultaneity with job loss. Both variables were lagged by two years to keep the models consistent when the survey changed from an annual to biennial design. Lagging income and health is important to attempt to account for some of pre-existing individual characteristics that predict both unemployment benefit receipt and health. To control for state-specific labor market conditions that may affect individual employment and health (34), we also used the state unemployment rate for the working-age population calculated from the CPS.

3.2 Methods

We estimated linear probability models (results were similar for logistic regression models) to estimate the effects of unemployment benefits on self-reported health among the pool of unemployed working-age respondents, controlling for individual characteristics, including health status and household income prior to job loss, as well as state characteristics. To test the robustness of our results, we estimated two alternative models that aim to further account for pre-existing differences between unemployment benefit recipients and non-recipients.

First, we implemented one-to-one nearest neighbor propensity score matching models (35). Propensity score matching is a statistical matching technique that seeks to create treatment and control groups comprised of individuals that share comparable observable characteristics. We match each unemployment benefit recipient in the PSID sample to an unemployed non-recipient that shares similar individual level characteristics in the year prior to job loss (as described above) and was unemployed during comparable state labor market conditions (see Appendix for further description of the method)(36).

However, even matched estimates may be biased by unobserved individual level differences. To further test the robustness of our results, we estimated two-stage least squares (instrumental variable) models that exploit variation in the likelihood of receiving unemployment benefits based on whether job loss occurred due to a business closure. The rationale for this approach is that business closures are generally unrelated to the characteristics of an individual worker. Since Federal Unemployment Insurance Program rules require benefit recipients to have lost their job through no fault of their own, individuals who experience job loss due to a business closure are more likely to receive unemployment benefits than individuals who lost their job for other reasons. We can therefore estimate the health effects of receiving unemployment benefits among a subsample of unemployed individuals who have greater probability of receiving unemployment benefits for reasons that are presumably unrelated to their prior health. We employ a two-stage least squares modelling approach where we instrument for unemployment benefit receipt using information on whether job loss was due to a business closure, first using the full pool of unemployment spells experienced by heads of household in the PSID during the sample period, and then using the propensity score matched subsample (see Appendix for further description of the methods)(36).

4. RESULTS

4.1 Descriptive statistics

Exhibit 1 shows descriptive statistics for the full sample of unemployment spells. There are some important differences between unemployment benefit recipients and non-recipients. Benefit recipients are more likely to be married, white, male, and/or have had comparatively higher household incomes, which is consistent with evidence from official government sources (17). By contrast, non-benefit recipients are more likely to be single and/or black. Unemployed individuals are more likely to receive benefits if they are jobless in states and years with higher unemployment rates.

<Exhibit 1. Descriptive statistics for the sample of unemployment spells>

Non-benefit recipients are also more likely to report poor health than unemployment benefit recipients, both in the year before job loss (21.2% compared to 15.3%, t-value=3.99) and in the year after job loss (25.8% compared to 18.4%, t-value=4.72) (Exhibit 2). Compared to benefit recipients, a slightly greater percentage of non-recipients who previously did not report poor health in the year before job loss reported poor health in the year after job loss (12.0% compared to 10.9%, t-value=0.94) (Data not shown).

<Exhibit 2. Percentage of individuals reporting poor health, before and after job loss>

4.2 Model results

Exhibit 3 summarizes the main results of two models that estimate the effect of unemployment benefit receipt on the probability of reporting poor health (full results from all models can be found in Appendix Table A1)(36). Simple unadjusted linear probability models that control only for poor health in the year before job loss suggest that receiving unemployment benefits is associated with a significant reduction of 4.6 percentage points in the probability of reporting poor health (Data not shown). In a linear probability model that controls for poor health in the year prior to job loss, marital status, race, education, household size, age, gender, household income in the year prior to job loss, state unemployment rates and state and year fixed effects, the estimate remains consistent, indicating that receipt of unemployment benefits is associated with a 4.7 percentage point significant reduction in the probability of reporting poor health (95% Confidence Interval: -7.5, -1.8) (Exhibit 3, column 1).

< Exhibit 3. Estimated effects of unemployment benefit receipt on probability of poor health, main model results>

A potential concern is that ex-ante differences between unemployment benefit recipients and non-recipients could bias the results, even after controlling for observable individual and state-level characteristics. We therefore estimated propensity score matching models. This left us with a matched sample of unemployment spells that does not reveal significant differences between the unemployment benefit and non-recipient groups in observable individual characteristics in the year prior to job loss (Appendix Exhibit A2)(36). The standardized bias is reduced considerably across the sample and across all covariates (Appendix Exhibit A3 and A4) (36).

The second column of Exhibit 3 summarizes estimated effects of unemployment benefit receipt based on the propensity score matched sample. Using this matched sample of benefit recipients and non-recipients, the fully-adjusted linear probability model indicates that unemployment benefits reduce the probability of reporting poor health by 3.0 percentage points (95% Confidence Interval: -6.6, 0.5). We find no statistically significant difference in the estimated effects of unemployment benefits between the two models shown, since the 95% confidence intervals estimated from the propensity score matched sample fully overlap with those estimated using the full sample.

As an additional robustness check, we estimated two-stage least square models that examine effects of unemployment benefits among those whose likelihood of receiving benefits is influenced by the fact that they lost their job due to a business closure. Results from the first stage indicate that workers losing their job due to business closure were significantly more likely to receive benefits. Among the pool of all unemployment spells, controlling for individual characteristics, losing a job due a business closure increases the probability of receiving unemployment benefits significantly by 15.8 percentage points (Appendix Exhibit A5)(36). Workers who lost their job due to a business closure, however, did not systematically differ compared to workers losing their job for other reasons in terms of health prior to job loss and other observable characteristics (Appendix Exhibit A6)(36).

The two right columns of Exhibit 4 show second-stage estimates from the two-stage least squares models. In line with our original models, unemployment benefits significantly reduce the probability of poor self-reported health. Although the magnitudes of the point estimates are large, the estimates are less precise and do not significantly differ from those in our original two models presented in Exhibit 3. Given the lack of precision, the magnitude of the effect should be cautiously interpreted, and emphasis should be on the direction of effect. Estimates may also not be generalizable to the broader unemployed sample since they reflect the local average treatment effect among the business closure subsample. Overall, however, results from 2SLS models are consistent with those from the two other modelling approaches and suggest that unemployment benefits are associated with better health among workers experiencing job loss.

<Exhibit 4. Estimated effects of unemployment benefit receipt on probability of poor health, all model results, 95% confidence intervals>

5. DISCUSSION

Estimating the health effects of unemployment benefits is challenging because recipients are often *a priori* better-off than those who do not receive unemployment benefits. Inferring causal effects by comparing the health of benefit recipients with non-recipients therefore requires great care. In this paper we use a variety of modelling strategies to examine the impact of unemployment benefits on the health of the unemployed. Although we still cannot claim a causal link between unemployment benefits and health, the estimates consistently indicate that unemployed individuals who receive benefits are at lower risk of reporting poor health in the year following job loss than comparable unemployed individuals who do not receive unemployment benefits.

Our objective was to examine whether unemployment benefits may potentially influence the health of the unemployed. Yet, the pre-existing health, wealth and educational differences between benefit recipients and non-recipients are themselves policy relevant, as they indicate significant inequalities in access to benefits. Unemployment benefits smooth consumption and provide an opportunity to search for suitable new employment (12, 37). Therefore, the observed socio-economic differences between benefit recipients and non-recipients are themselves of concern as they suggest that the program disproportionately benefits socioeconomically advantaged workers more than it benefits vulnerable workers from lower socioeconomic status.

Unemployment benefits may affect health through *income* by helping to maintain consumption patterns or reducing financial stress, or through *time* by subsidising leisure. Income is a well-known health determinant (38); there are a multitude of ways by which income could affect health. For example, income may allow individuals to consume healthy goods and services, such as fruits and vegetables that are often more expensive than unhealthy foods (39). Income may also enable the unemployed to access health care. In our United States sample, most individuals who experienced job loss were also likely to lose access to their employer-based health insurance. However, while individuals who lose their job are able to keep their employer-based health insurance under the Consolidated Omnibus Budget Reconciliation Act (COBRA) of 1985, they are responsible for paying the full insurance premium, making insurance only accessible to those with financial liquidity. A review found that only 14% of eligible individuals maintained their employer-based insurance coverage in 2010, while 57% became uninsured (40).

Income-related health effects of unemployment benefits may alternatively occur through some non-consumption related pathway that is still a result of the short-term income subsidy provided by benefits. For example, it is possible that unemployment benefits may have an independent psychological effect by providing comfort and security to job losers.

Although income may play an important role, there are alternative explanations for the impact of unemployment benefits on health. The canonical Grossman model of demand for health posits that demand for time-intensive health promoting activities will increase as the price of engaging in these activities decreases (41). Time spent working increases income, which allows individuals to purchase health inputs such as healthy food, but at the same time, working reduces time to invest in health promoting activities like exercise, or may even harm health as a result of exposure to adverse working conditions. Individuals who are not working, however, may have more leisure time available that can be used for health promoting, time consuming activities like exercise. Unemployment benefits may therefore protect health by subsidizing time out of work and providing the unemployed with additional time to engage in health promoting leisure activities. This notion is consistent with research suggesting that unemployment benefits may lengthen unemployment duration by underwriting leisure time (23, 42).

Our results also offer some insight into the potential mechanisms linking job loss to health. The finding that unemployment benefits improve self-rated health suggests that income losses and financial uncertainty are potential mechanisms through which unemployment influences health. In the absence of benefits, some unemployed individuals may feel distressed or be unable to pay for health promoting goods and services. Unemployment benefits, alternatively, may help the unemployed to cope with some of the stress associated with financial insecurity.

There are a number of limitations in our study. First, the estimated effects of unemployment benefits are only generalizable to the sample of heads of households included in the analysis. Additionally, while the propensity score matching and two-stage least squares analyses aim to provide additional evidence on whether benefit receipt plays a role in the causal pathway linking job loss to health, neither method is able to establish causality. In the case of the propensity score matching models, it is possible that the treatment or control groups are biased by unmeasured factors that are correlated with both benefit receipt and health. Likewise, the two-stage least squares analysis estimates the effect of receiving unemployment benefits specifically among those individuals whose probability of receiving benefits is altered by having lost a job due to a business closure. The estimate therefore reflects the so-called 'local average treatment effect' among this particular group and may not be generalizable to the broader unemployed population. Nevertheless, we believe both approaches serve as important tests of the relationship between benefit receipt and health. Finally, although self-rated health has been shown to be a strong predictor of objective measures of health, including the risk of death (31-33), data on other indictors of health would have provided a more nuanced analysis of the potential mechanisms linking benefits to health. Unfortunately, PSID did not collect detailed information on the incidence and timing of other health outcomes for a sufficiently long period.

Overall, this study provides some evidence that receiving unemployment benefits may have positive effects on the health of the unemployed. These findings are important for policy. Policymakers have repeatedly introduced changes to state unemployment benefit program components, such as the maximum allowable weekly benefit amount and duration of benefit receipt. Our study suggests, however, that policy makers need to consider strategies to increase the take-up of unemployment benefits among the unemployed. For example, a recent policy reform was introduced to increase benefit access by altering the base period used to calculate eligibility. However, this reform has had limited impacts on take-up of state benefit programs (43). The relatively low take up of benefits may be partly attributable to the stigma associated with claiming unemployment benefits, with many eligible individuals choosing not to apply, highlighting the need of policies to change attitudes towards benefits. Likewise, around half of the unemployed are unaware of their eligibility (18); increasing awareness of unemployment benefit rules, therefore, would be crucial to ensure that the programme reaches those in greatest need.

During the financial crisis, as unemployment rates rose, the United States government responded with an unprecedented extension of unemployment insurance benefits from the standard 26 week duration to a maximum of 99 weeks (44); the Emergency Unemployment Compensation program expired at the end of 2013. While there was considerable debate in Congress around the time of expiration over whether to continue benefit extensions, there is no evidence that the health effects of maintaining unemployment benefits were taken into account (45). This study suggests that policymakers should consider potential health consequences of future unemployment benefit extensions, cuts and program reforms.

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EXHIBIT LIST

EXHIBIT 1 (Table)

Caption: Descriptive statistics for the sample of unemployment spells

Source: Authors’ calculations based on Panel Study of Income Dynamics and Current Population Survey data.

Notes: SD=Standard deviation

EXHIBIT 2 (Figure)

Caption: Percentage of individuals reporting poor health, before and after job loss

Source: Authors’ calculations based on Panel Study of Income Dynamics data.

EXHIBIT 3 (Table)

Caption: Estimated effects of unemployment benefit receipt on probability of poor health, main model results

Source: Authors’ calculations based on Panel Study of Income Dynamics and Current Population Survey data.

Notes: Robust standard errors in parenthesis. Models include marital status, race, education, number in household, age, gender, logged real household income, state unemployment rates and state and year fixed effects.

EXHIBIT 4 (Figure)

Caption: Estimated effects of unemployment benefit receipt on probability of poor health, all model results, 95% confidence intervals

Source: Authors' calculations based on Panel Study of Income Dynamics and Current Population Survey data.

Notes: Models include marital status, race, education, number in household, age, gender, logged real household income, state unemployment rates and state and year fixed effects.

TABLES AND FIGURES

EXHIBIT 1. Descriptive statistics for the sample of unemployment spells

	Unemployment benefit recipient		Non-unemployment benefit recipient		All unemployment spells	
	Mean	SD	Mean	SD	Mean	SD
Male	69.0%	0.5	56.2%	0.5	58.8%	0.5
Age	40.4	11.2	39.5	13.2	39.7	12.8
Married	44.1%	0.5	31.4%	0.5	34.0%	0.5
Single	27.6%	0.4	38.4%	0.5	36.2%	0.5
Widowed	3.4%	0.2	5.1%	0.2	4.8%	0.2
Divorced	17.6%	0.4	16.8%	0.4	17.0%	0.4
Separated	7.3%	0.3	8.2%	0.3	8.0%	0.3
White	51.6%	0.5	39.4%	0.5	41.9%	0.5
Black	41.1%	0.5	56.2%	0.5	53.1%	0.5
Other	6.9%	0.3	3.7%	0.2	4.3%	0.2
High School or less	72.8%	0.4	76.9%	0.4	76.1%	0.4
College	26.3%	0.4	21.5%	0.4	22.5%	0.4
Post-Graduate	0.8%	0.1	1.6%	0.1	1.4%	0.1
Household size	2.9	1.6	2.7	1.7	2.8	1.7
Total family income in year before unemployment spell	38,149	31,121	30,133	43,496	31,783	41,377
Working age state unemployment rate in year of unemployment spell	5.1	1.6	4.7	1.6	4.8	1.6
Share of unemployment spell sample	20.6%		79.4%		100.0%	

EXHIBIT 2 Percentage of individuals reporting poor health, before and after job loss

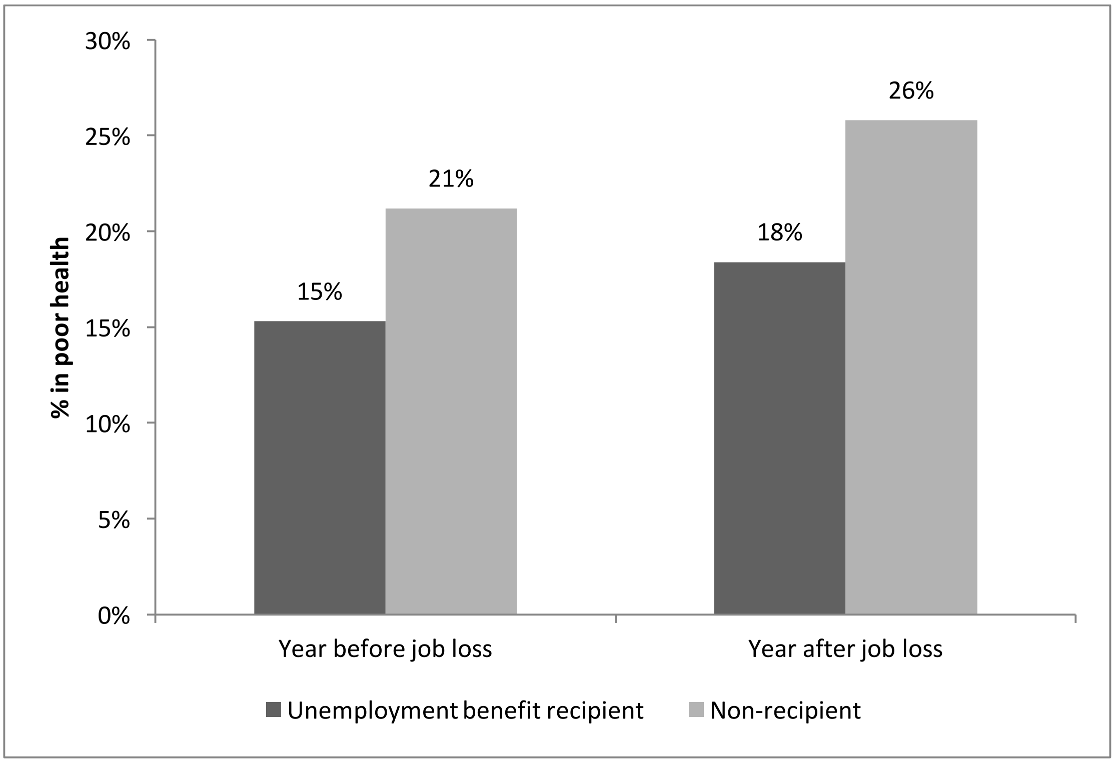


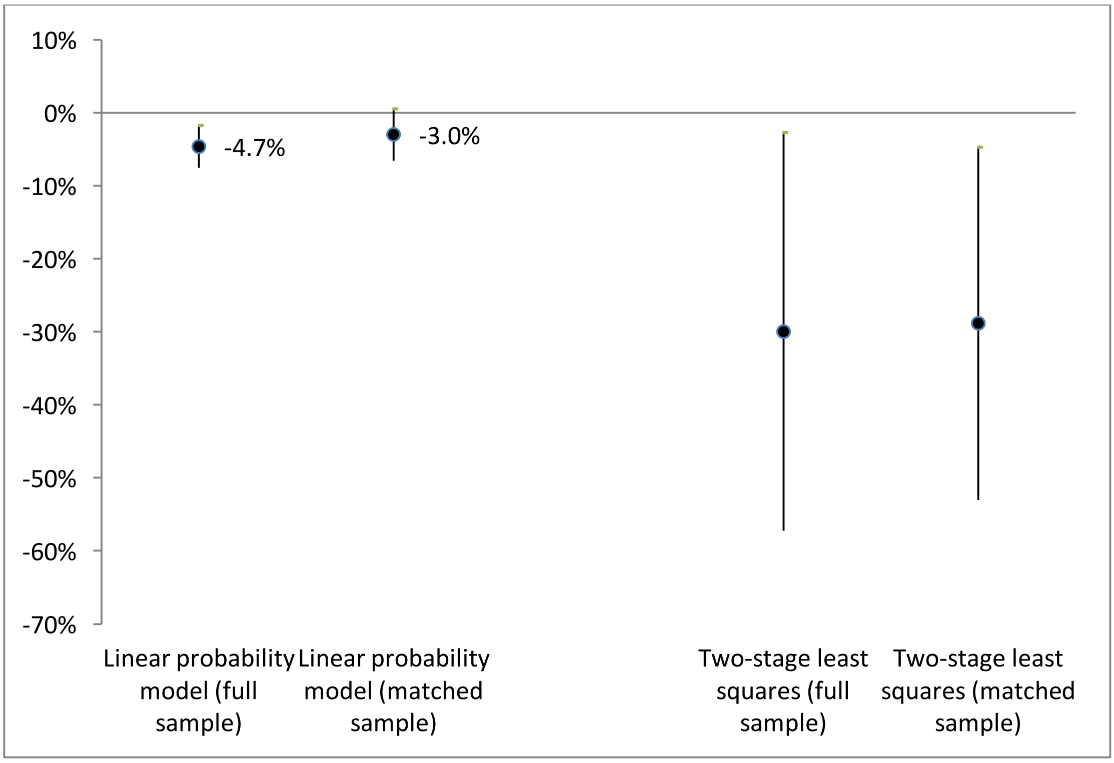
EXHIBIT 3. Estimated effects of unemployment benefit receipt on probability of poor health, main model results

	(1)	(2)
	Linear probability model (all unemployment spells)	Linear probability model (propensity score matched sample)
Unemployment benefit receipt	-0.0466***	-0.0304*
	(0.0147)	(0.018)
Poor health in the year prior to job loss	0.437***	0.383***
	(0.0184)	(0.0327)
Observations	4,247	1,750
R-squared	0.237	0.197

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in parenthesis. Models include marital status, race, education, number in household, age, gender, logged real household income, state unemployment rates and state and year fixed effects.

EXHIBIT 4 Estimated effects of unemployment benefit receipt on probability of poor health, all model results, 95% confidence intervals



Appendix explanation of methodologies

Propensity score matching description

Propensity score matching creates comparable treatment and control groups by adjusting for pre-treatment observable differences between a group of treated and a group of untreated.

To do this, we first estimate a probit regression that predicts the propensity to be included in the treatment group according to a set of covariates. That is, we predict the likelihood of being an unemployment benefit recipient conditional on health 2 years prior, marital status, race, education, household size, gender, household income 2 years prior, age, and working-age state unemployment rates in the year of the unemployment spell. Using the estimated pscores, we can form a control group that is comparable in observable characteristics but did not receive benefits.

Comparing the matched treatment and control groups, we see (as shown in Appendix Exhibits A2, A3 and A4) that the control group exhibits significantly less bias after matching. We then implement linear probability and 2SLS models using this matched subsample.

Two-stage least squares (instrumental variable) methodological description

Our objective is to estimate the average causal effect of UI receipt on self-reported health for individuals that experienced job loss in the previous year. Alternatively, this can be thought of as the mean effect of a treatment on a treated population, where UI is the treatment and unemployed non-UI recipients are the control group. The average treatment effect is the difference between the two groups, provided that unemployed workers in the treatment group are identical to unemployed workers in the control group.

We start with the following basic specification:

$$\Delta = E(Y_{i,1} \mid UI_{i,1} = 1) - E(Y_{i,1} \mid UI_{i,1} = 0)$$

Here, $Y_{i,1}$ is an unemployed individual’s self-reported health in the year after job loss. The parameter Δ captures the difference in health between jobless individuals who received UI (UI=1) compared to that of jobless individuals who did not received UI (UI=0).

Because we do not observe the counterfactual (i.e. the effect of UI receipt for those who did not actually receive UI) we need to identify a control group of unemployed non-UI recipients. For an individual i’ in the control group (i.e. not in receipt of benefits) with the same observed individual characteristics as someone in the treatment group who did receive UI, we assume:

$$E(Y_{i,1} \mid X_{i,t}, Y_{i,0}, UI_{i,1} = 0) = E(Y_{i',1} \mid X_{i',t}, Y_{i',0}, UI_{i',1} = 0)$$

where X is a vector of characteristics, including age, gender, race, education, marital status, household size and previous income level pre-job loss; and $Y_{i,0}$ is self-reported health in a previous time period. We can identify the average UI treatment effect by estimating the following naïve equation in a linear probability model that controls for many of the observable factors that may differ between the treatment and control groups:

$$Y_{i,t} = \alpha + X_{i,t}\pi + UI_{i,t-1}\Delta + S + T + UR_{s,t-1} + \varepsilon_{i,t} \qquad (1)$$

Where Y_{it} is health of unemployed individual i at time t, X is a vector of control variables associated with receipt of unemployment benefits, UI is a binary indicator for whether the individual received UI in the previous year, S is a set of State fixed effects, T is a set of year fixed effects, UR is the unemployment rate in the State of residence in the year of job loss, and ε is the standard error.

The assumption of comparability between UI recipients and non-recipients, however, is difficult to meet; although many of the variables selecting individuals into UI may be captured by X, the equation above is insufficient to identify the effect of UI receipt on health because UI will be endogenous with health if there are additional unobserved characteristics that correlate with both health and UI receipt. In this case, OLS may produce biased estimates of the causal effect of benefits on health.

To address the potential endogeneity of UI receipt we use a two-stage least squares (2SLS) approach that exploits exogenous variation in a variable that predicts UI receipt but is not included in the main equation predicting poor health, and is not correlated with ε_i. We experimented with a variety of possible instruments, including State laws on maximum unemployment benefit levels in a State and year, and State-level implementation of a policy that alters the base period used to define UI monetary eligibility, known as the Alternate Base Period (ABP). However, neither is a sufficiently strong predictor of benefit receipt in our PSID sample. In the case of maximum benefit generosity, it is possible that the unemployed are unaware of small variations in state UI maximum benefits when deciding whether to apply for benefits, or that changes during the sample period are too small to generate changes in claiming behavior. Likewise, State implementation of ABP is a weak predictor of UI receipt for all but low-income workers, who are only marginally represented in our small sample.

Our preferred model specification utilizes a binary variable indicating whether job loss was the result of a business closure as the IV. During the sample period, 8.1% of unemployment spells were attributable to business closure among those with data available on the cause of job loss; 44.1% reported quitting their job, while 31.0% were laid off. The rationale for our approach is that Federal UI rules imply that workers who involuntarily lose their job due to business closure (and other involuntary causes) are more likely to be eligible to receive UI than workers that experience job loss due to other reasons such as quitting without good cause or being fired. We assume business closures to be exogenous, as they themselves are not due strictly to an individual person's characteristics (Strully, 2009, Salm, 2009, Brand et al., 2008).

We use linear 2SLS models where the first stage equation takes the following form:

$$UI_{i,t-1} = \alpha + X_{i,t}\pi + BC_{i,t-1}\Delta + S + T + UR_{s,t-1} + \varepsilon_{i,t-1} \qquad (2)$$

Where BC is whether job loss occurred as a result of a business closure. In the second stage, the predicted level $\hat{U}I$ is then substituted into the original equation:

$$Y_{i,t} = \alpha + X_{i,t}\pi + \hat{U}I_{i,t-1}\Delta + S + T + UR_{s,t-1} + \varepsilon_{i,t} \qquad (3)$$

Where $Y_{i,t}$ is the probability that unemployed individual i would report poor health at time t. Effectively, this IV approach allows us to estimate the effect of UI receipt on the likelihood of poor health in a treated sample of unemployed workers with increased likelihood of receiving benefits, but whose characteristics do not differ from a control sample of unemployed workers who are less likely to be eligible for benefits.

Appendix Exhibits

Appendix Exhibit A1. Full model results

VARIABLES	(1) Linear probability model (full sample)	(2) Linear probability model (matched sample)	(3) Two-stage least squares (full sample)	(4) Two-stage least squares (matched sample)
Received unemployment benefits	-0.0466***	-0.0304*	-0.300**	-0.289**
	(0.0147)	(0.0180)	(0.139)	(0.123)
Poor health (t-2)	0.437***	0.383***	0.428***	0.392***
	(0.0184)	(0.0327)	(0.0162)	(0.0268)
Marital status (Married)	.	.	.	.
Marital status (Single)	-0.00126	0.00184	-0.00810	-0.00539
	(0.0203)	(0.0302)	(0.0212)	(0.0314)
Marital status (Separated)	0.0655*	0.142**	0.0576*	0.141**
	(0.0352)	(0.0672)	(0.0331)	(0.0580)
Marital status (Divorced)	0.00348	-0.00413	0.00614	-0.0112
	(0.0214)	(0.0303)	(0.0217)	(0.0319)
Marital status (Widowed)	0.00130	0.00570	0.000943	0.00247
	(0.0284)	(0.0449)	(0.0272)	(0.0427)
Race (White)	.	.	.	.
Race (Black)	0.0173	0.00581	0.00590	0.00607
	(0.0155)	(0.0240)	(0.0171)	(0.0244)
Race (Other)	0.0142	0.0176	0.0305	0.0119
	(0.0311)	(0.0408)	(0.0325)	(0.0400)
Education (High School)	.	.	.	.
Education (College)	-0.0438***	-0.0481**	-0.0434***	-0.0494**
	(0.0148)	(0.0220)	(0.0160)	(0.0235)
Education (More than college)	-0.0734	-0.0899	-0.115**	-0.0804
	(0.0473)	(0.0766)	(0.0565)	(0.101)
Household size	0.0139***	0.0136**	0.0148***	0.0160**
	(0.00416)	(0.00682)	(0.00412)	(0.00675)
Gender (1=male)	0.00607	-0.00932	0.0139	-0.00883
	(0.0154)	(0.0254)	(0.0161)	(0.0257)
Natural log of family income (t-2)	-0.000194	-0.0176	0.0101	-0.0209*
	(0.00476)	(0.0110)	(0.00766)	(0.0113)
Age	0.00471***	0.00380***	0.00426***	0.00375***
	(0.000591)	(0.000891)	(0.000647)	(0.000902)
State working age	-0.00876	-0.00935	-0.00304	-0.00768

unemployment rate (t-1)				
	(0.00561)	(0.00880)	(0.00656)	(0.00915)
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	-0.287***	0.0827	-0.210	0.511***
	(0.0820)	(0.120)	(0.242)	(0.182)
Observations	4,247	1,750	4,247	1,750
R-squared	0.237	0.197	0.184	0.098

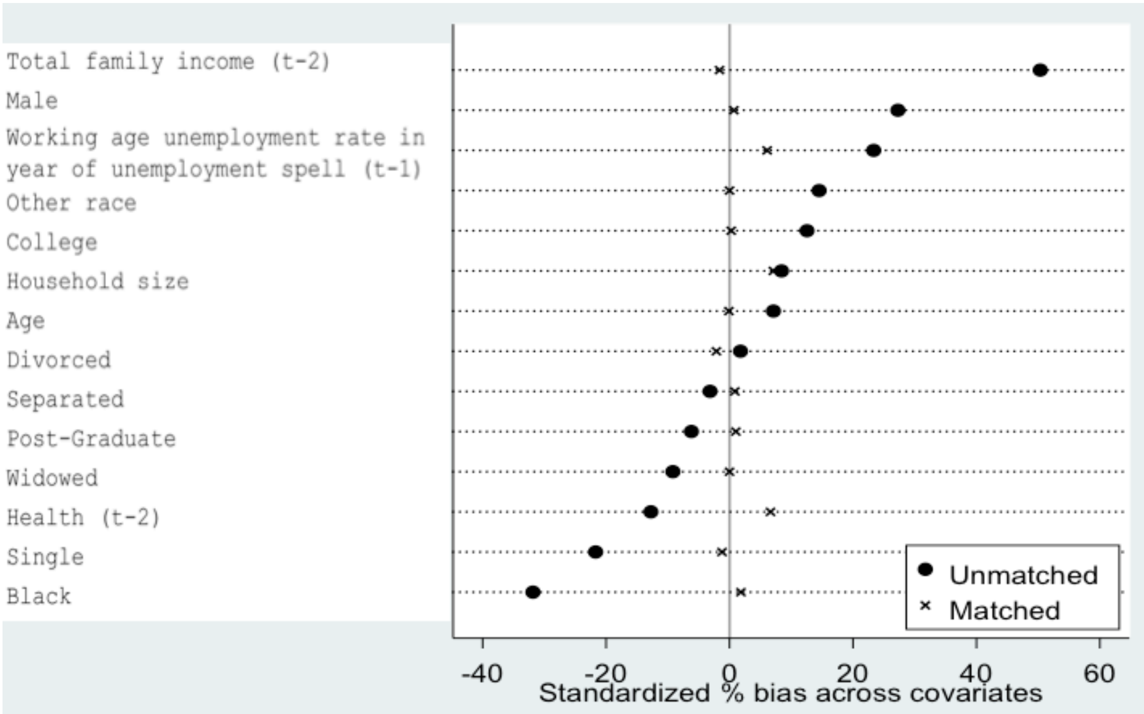
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Exhibit A2. Comparison between treated (unemployment benefit recipients) and control (non-recipients) among matched and unmatched sample

		Mean					
Variable		**Treated**	**Control**	**%bias**	**% bias reduced**	**T-test**	**p-value**
Unemployment benefit receipt	Unmatched	1	0	.		.	.
	Matched	1	0	.	.	.	.
Health (t-2)	Unmatched	2.4663	2.5999	-12.7		-3.26	0.001
	Matched	2.4663	2.3966	6.6	47.8	1.43	0.153
Single	Unmatched	0.28457	0.38642	-21.7		-5.59	0
	Matched	0.28457	0.29029	-1.2	94.4	-0.26	0.792
Widowed	Unmatched	0.03314	0.0516	-9.2		-2.28	0.023
	Matched	0.03314	0.03314	0	100	0	1
Divorced	Unmatched	0.17486	0.16815	1.8		0.47	0.638
	Matched	0.17486	0.18286	-2.1	-19.3	-0.44	0.663
Separated	Unmatched	0.072	0.08037	-3.2		-0.82	0.413
	Matched	0.072	0.06971	0.9	72.7	0.19	0.852
Black	Unmatched	0.408	0.56524	-31.8		-8.37	0
	Matched	0.408	0.39886	1.9	94.2	0.39	0.697
Other	Unmatched	0.072	0.03885	14.5		4.19	0

	Matched	0.072	0.072	0	100	0	1
College	Unmatched	0.25714	0.20433	12.6		3.39	0.001
	Matched	0.25714	0.256	0.3	97.8	0.05	0.956
Post-Graduate	Unmatched	0.00914	0.01601	-6.2		-1.51	0.131
	Matched	0.00914	0.008	1	83.4	0.26	0.796
Household size	Unmatched	2.8617	2.7233	8.4		2.2	0.028
	Matched	2.8617	2.7451	7.1	15.8	1.52	0.129
Male	Unmatched	0.68914	0.55813	27.3		7.05	0
	Matched	0.68914	0.68571	0.7	97.4	0.15	0.877
Total family income (t-2)	Unmatched	10.217	9.5893	50.3		11.84	0
	Matched	10.217	10.237	-1.6	96.8	-0.42	0.677
Age	Unmatched	40.425	39.561	7.1		1.79	0.074
	Matched	40.425	40.437	-0.1	98.7	-0.02	0.985
Working age unemployment rate in year of unemployment spell (t-1)	Unmatched	5.0003	4.6444	23.4		6.14	0
	Matched	5.0003	4.9074	6.1	73.9	1.27	0.204

Appendix Exhibit A3 Comparison of reduction in bias before and after matching



Appendix Exhibit A4. Balancing statistics between unmatched and matched samples

Sample	Pseudo R2	LR chi2	p>chi2	MeanBias	MedBias
Raw	0.063	272.27	0	16.4	12.6
Matched	0.003	6.4	0.955	2.1	1.1

Appendix Exhibit A5. First stage regressions predicting the probability of receiving unemployment benefits

VARIABLES	(1) Full sample	(2) Matched sample
Job loss due to business closure	0.158***	0.257***
	(0.0222)	(0.0409)
Poor health (t-2)	-0.0339**	0.0306
	(0.0155)	(0.0344)
Marital status (Married)	.	.
Marital status (Single)	-0.0266	-0.0205
	(0.0209)	(0.0405)
Marital status (Separated)	-0.0333	-0.0127
	(0.0330)	(0.0752)
Marital status (Divorced)	0.00644	-0.0331
	(0.0217)	(0.0412)
Marital status (Widowed)	-0.00590	-0.00849
	(0.0273)	(0.0554)
Race (White)	.	.
Race (Black)	-0.0471***	-0.00521
	(0.0160)	(0.0317)
Race (Other)	0.0735**	-0.0159
	(0.0314)	(0.0518)
Education (High School)	.	.
Education (College)	0.00481	0.00800
	(0.0161)	(0.0306)
Education (More than college)	-0.159***	0.0548
	(0.0520)	(0.131)
Household size	0.00335	0.0122
	(0.00411)	(0.00864)
Gender (1=male)	0.0269*	0.00425
	(0.0156)	(0.0333)
Natural log of family income (t-2)	0.0402***	-0.0163
	(0.00516)	(0.0145)
Age	-0.00185***	-0.000281

	(0.000601)	(0.00117)
State working age unemployment rate (t-1)	0.0237***	0.00920
	(0.00579)	(0.0118)
State fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Constant	-0.426	0.116
	(0.397)	(0.517)
Observations	4,247	1,750
R-squared	0.100	0.086
F-statistic	50.99	39.42

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Exhibit A6. Comparison of business closure and other job losers

	Business closure		Other causes of job loss		Total	
	Mean	SD	Mean	SD	Mean	SD
Health (t)	2.660	1.081	2.717	1.154	2.712	1.149
Poor health (t)	0.222	0.416	0.245	0.430	0.243	0.429
Health (t-2)	2.567	1.063	2.579	1.082	2.578	1.081
Poor health (t-2)	0.201	0.401	0.200	0.400	0.200	0.400
Male	0.631	0.483	0.584	0.493	0.588	0.492
Age	41.2	11.4	39.5	12.9	39.7	12.8
Married	0.369	0.483	0.338	0.473	0.340	0.474
Single	0.278	0.449	0.369	0.483	0.362	0.481
Widowed	0.059	0.236	0.047	0.211	0.048	0.213
Divorced	0.198	0.399	0.167	0.373	0.170	0.375
Separated	0.096	0.295	0.079	0.270	0.080	0.272
White	0.436	0.497	0.418	0.493	0.419	0.493
Black	0.543	0.499	0.530	0.499	0.531	0.499
Other	0.019	0.136	0.045	0.208	0.043	0.204
High School or less	0.802	0.399	0.757	0.429	0.761	0.427
College	0.187	0.391	0.228	0.420	0.225	0.418
Post-Graduate	0.011	0.103	0.015	0.120	0.014	0.119
Household size	2.805	1.651	2.751	1.655	2.755	1.654
Total family income (t-2)	32202	36510	31746	41778	31783	41376
Working age unemployment rate in year of unemployment spell (t-1)	4.9	1.6	4.8	1.6	4.8	1.6